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Benchmarking, Monitoring, Observability and Experimenting for Big Data and Machine Learning Systems

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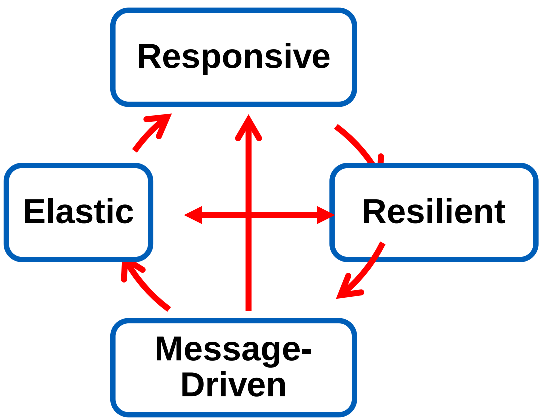
Learning objectives

- **Able to analyze the role of measurement, monitoring and observability in real-world cases for R3E**
- **Understand and develop methods with key steps and important tools for benchmarking, monitoring, observability and experimenting**
- **Able to apply these methods for big data/ML systems**

The role of measurement, monitoring and observability

Reactive systems – an architectural style for R3E?

Reactive systems



Source: https://www.reactivemanifesto.org/

For R3E abilities, big data/ML systems can be designed with ”reactive systems” principles:

- **Responsive:**
  - capture and respond to quality indicators, quality of analytics
- **Resilient:**
  - deal within failures
- **Elastic:**
  - deal with different workload and quality of analytics
- **Message-driven:**
  - allow loosely coupling, isolation, asynchronous

Development vs Runtime activities

Design, test and benchmark R3E

- R3E for individual components
- model/capture complex dependencies
- design logs, metrics and traces for capturing states and complex dependencies

Monitoring/Observability and Runtime adaptation

- runtime monitoring and observability
- states, performance and failure analytics
- runtime controls (constraints, rules, actions)

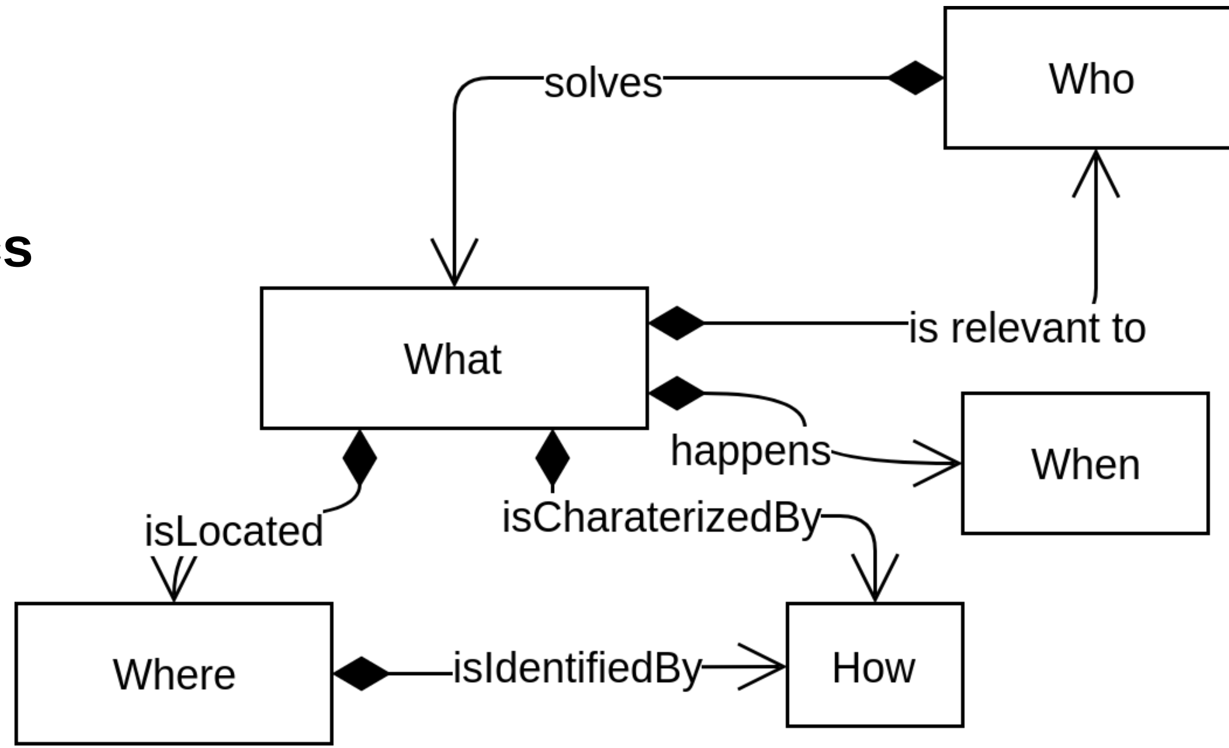
Measurement, Monitoring and Observability for R3E

- **Instrumentation and sampling**
  - instrumentation: insert probes into systems to measure system behaviors directly or produce logs
  - sampling: use components to sample system behaviors
- **Monitoring**
  - perform sampling or instrumentation to collect and share metrics, logs, traces; visualize what has been happened
- **Observability**
  - evaluate and interpret measurements for specific contexts
  - understand and explain the systems states, dependencies, etc.

Methods

What/Which, Where, When, Who and How

Understand W4H aspects for analytics of big data/ML systems



Key steps – What/Which

- **Understand and identify indicators/metrics characterizing big data/ML systems**
- **Common metrics and specific (ML)ones**
  - different relevance/importance based on specific contexts
- **Most critical problems are due to complex dependencies that are not common**
  - Root cause analysis will be tricky
- **For which purposes?**
  - SRE, benchmarking, Test-Driven Development (TDD)

Key steps – Where and When

- **Where: as a “ space” dimension**
  - Tightly coupled or isolated/loosely coupled
  - Identify the where
    - software/system layers, components and systems boundaries
    - dependencies among components
- **When: as a „time“ dimension**
  - Design, Test/Training, Runtime (DevOps)
  - Further divided into sub states

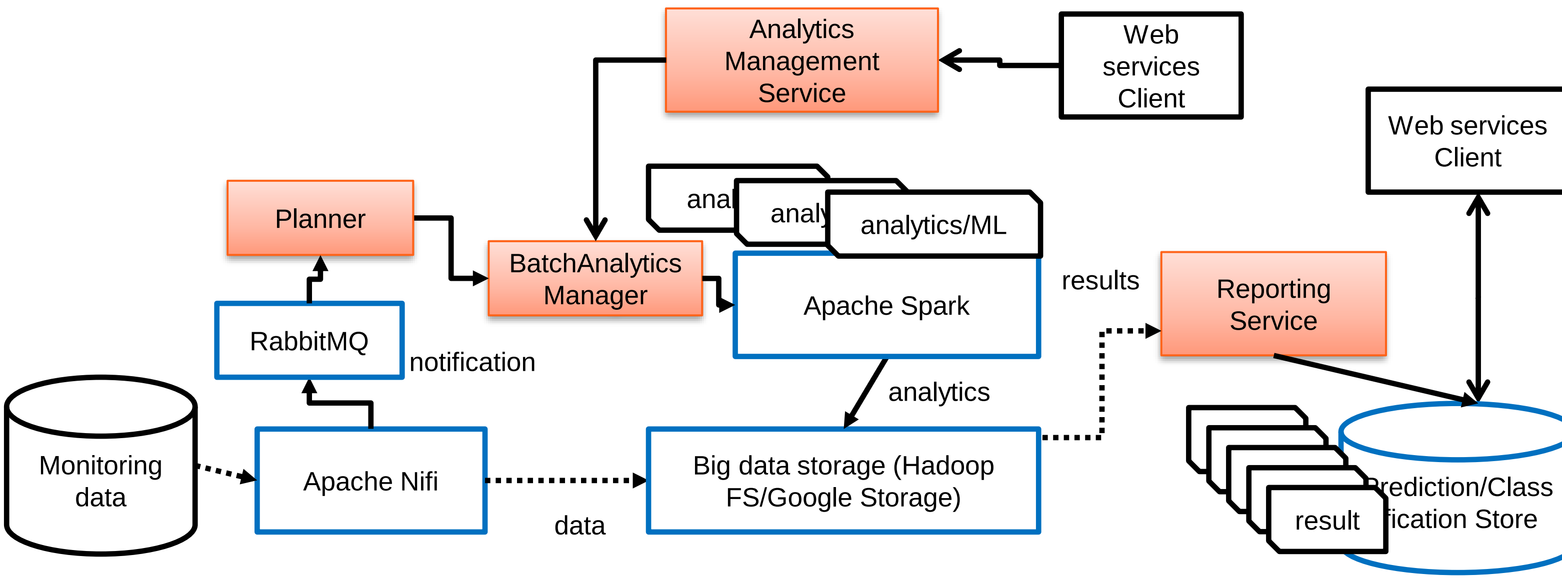
Key steps - How

- **Characterize dependencies among components**
  - Include also data, software artefacts and execution environments
- **Select tools for capturing metrics**
- **Understand what kind of changes/designs we must do**
- **Do monitoring and analysis**
- **Integrate many types of data for monitoring and observability**

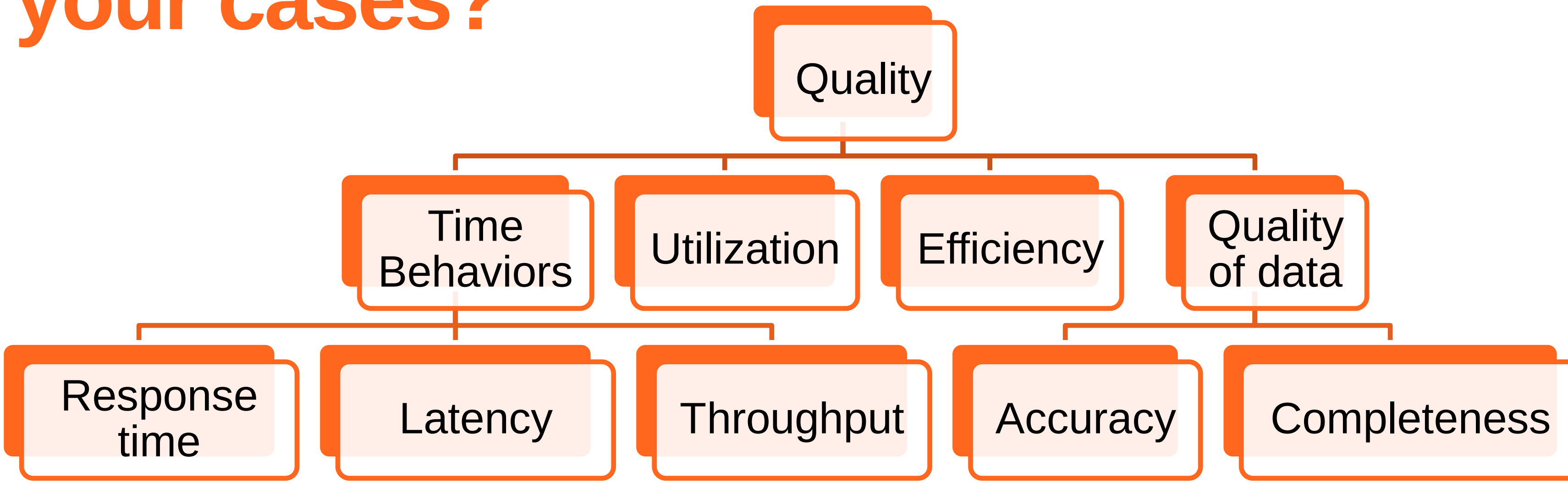
Apply W4H for dealing with benchmarking, monitoring, validation and experimenting

- **Determines clearly system boundaries**
  - the system under study, the system used to judge, and the environment
- **Understands dependencies**
  - among components in distributed big data/ML systems in distributed computing platforms
  - single layer as well as cross-layered dependencies
- **Determines types of metrics and failures and break down problems along the dependency path (how)**

Boundaries and dependencies?



What are the most critical metrics for your cases?



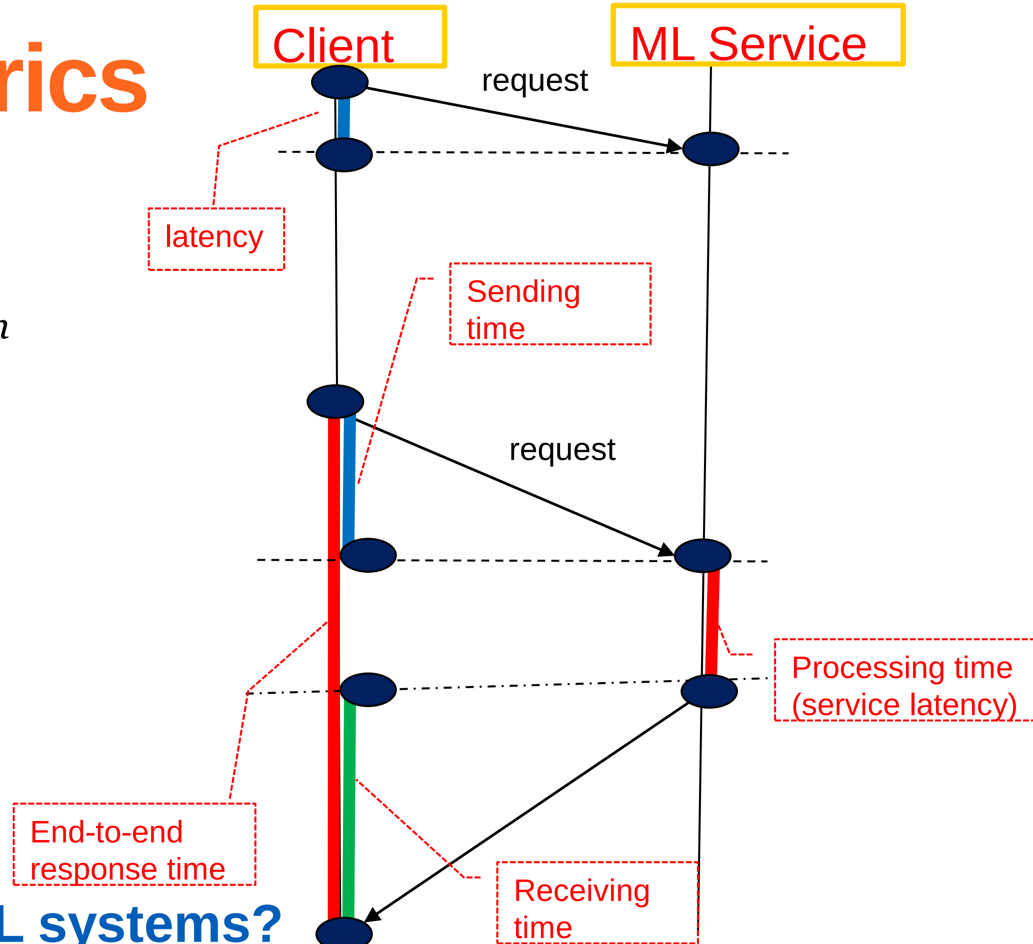
Industry view: https://guidingmetrics.com/content/cloud-services-industrys-10-most-critical-metrics/
NIST: https://www.nist.gov/sites/default/files/documents/itl/cloud/RATAX-CloudServiceMetricsDescription-DRAFT-20141111.pdf

Contradiction/Tradeoffs between Efficiency versus Resiliency

Common performance metrics

- **Timing behaviors**
  - Communication
    - *Latency/Transfer time*
    - *Data transfer rate, bandwidth*
  - Processing
    - *Response time (service latency/time)*
    - *Throughput*
- **Utilization**
  - Network utilization
  - CPU utilization
  - Service utilization
- **Efficiency/Scalability**
  - Concurrent Executions

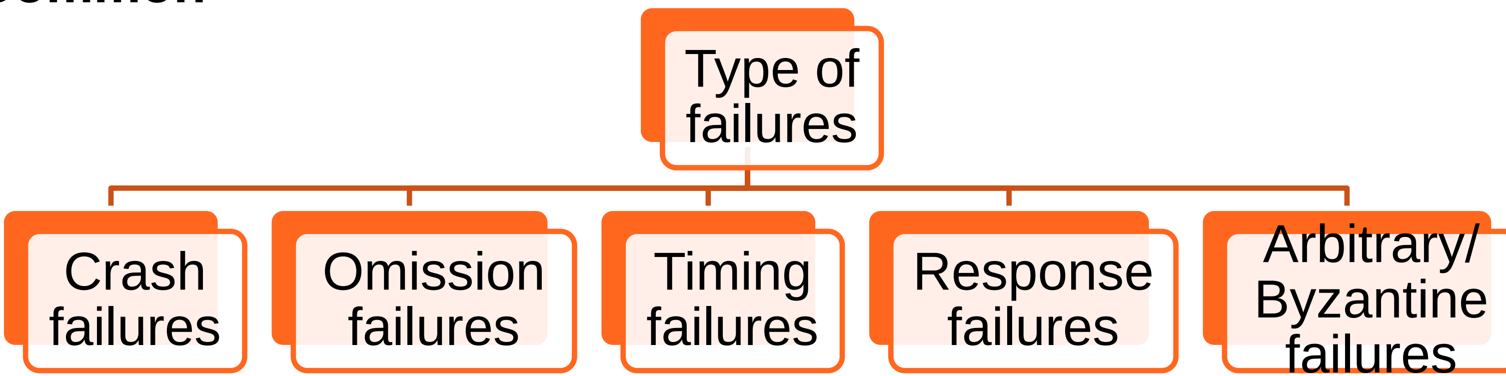
Examples



are they enough for big data/ML systems?

Types of Failure

Common



But unforeseen failures cannot be determined in advance → design for handling failure

Check:https://arxiv.org/pdf/1910.11015.pdf for a "Taxonomy of Real Faults in Deep Learning Systems"

Data Quality

- **Completeness**
- **Timeliness**
- **Currency**
- **Validity**
- **Format**
- **Accuracy**
- **Data Drift**

Metrics for ML models

- **Concept drift**
  - (https://en.wikipedia.org/wiki/Concept_drift)
- **Confusion matrix**
- **Accuracy**
- **Loss**
- **True positive rate**
- **False positive rate**
- **F1 Score/F-measure**
- **Etc.**

(see https://towardsdatascience.com/metrics-to-evaluate-your-machine-learning-algorithm-f10ba6e38234)

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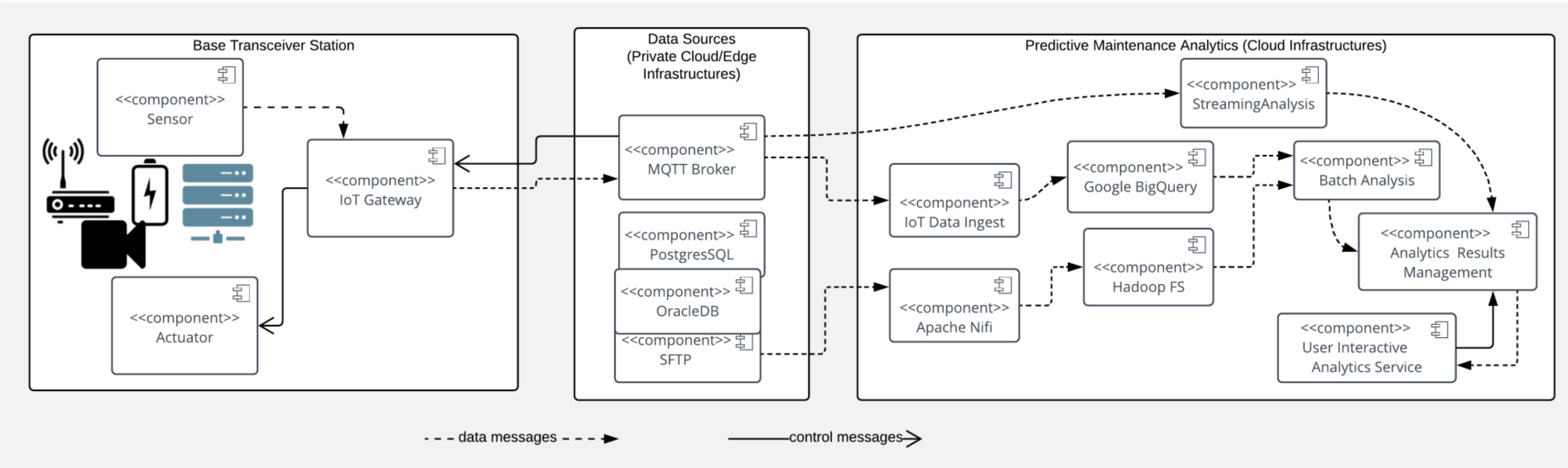
Benchmarking, Observability and R3E Handling

Benchmarking

- **Benchmark: for comparing big data/ML systems w.r.t. selected (standard/common) workloads**
- **Where to be benchmarked**
  - benchmark individual subsystems: message brokers and data ingestion, databases and ingestion/query, data processing, ML models, serving platform
- **What to be benchmarked**
  - data ingestion throughput, processing throughput and time, component CPU and memory
  - training and inferencing time and accuracy

Benchmarking

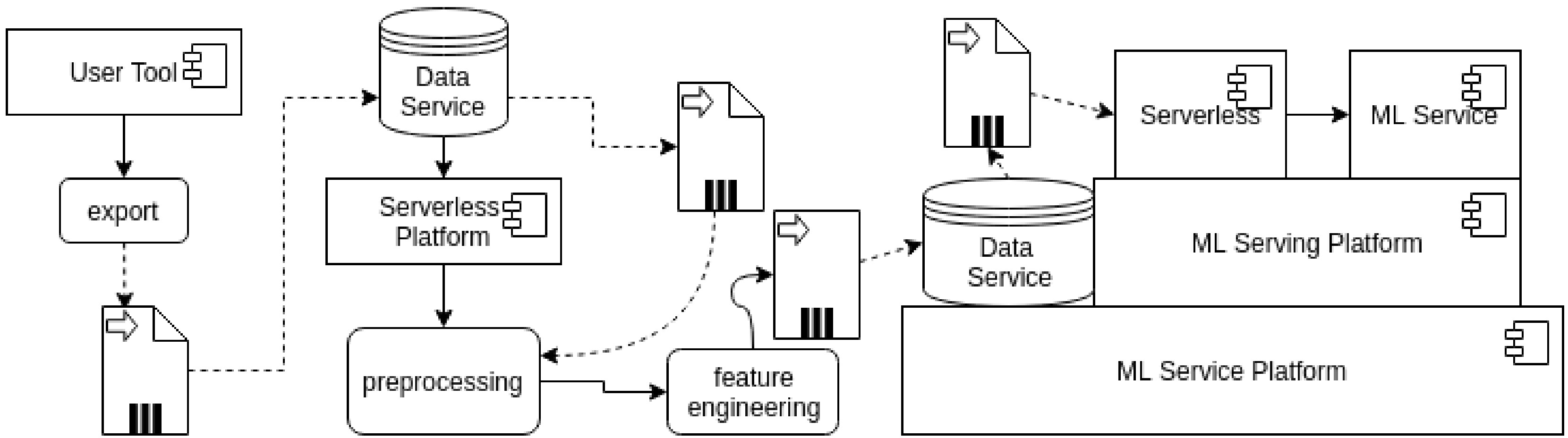
What should we do for a big data system?



Check: https://www.sciencedirect.com/science/article/pii/S0140366419312344
https://www.benchcouncil.org/BigDataBench/

Benchmarking

If you have an end-to-end ML system, does it make sense to benchmark the whole system?



Benchmarking - ML

Examples:

Benchmark results (minutes)							
Image classification	**Image segmentation (medical)**	**Object detection, light-weight**	**Object detection, heavy-weight**	**Speech recognition**	**NLP**	**Recom-mendation**	**Reinforce-ment Learning**
ImageNet	KiTS19	COCO	COCO	LibriSpeech	Wikipedia	1TB Clickthrough	Go
ResNet	3D U-Net	SSD	Mask R-CNN	RNN-T	BERT [1]	DLRM	Minigo

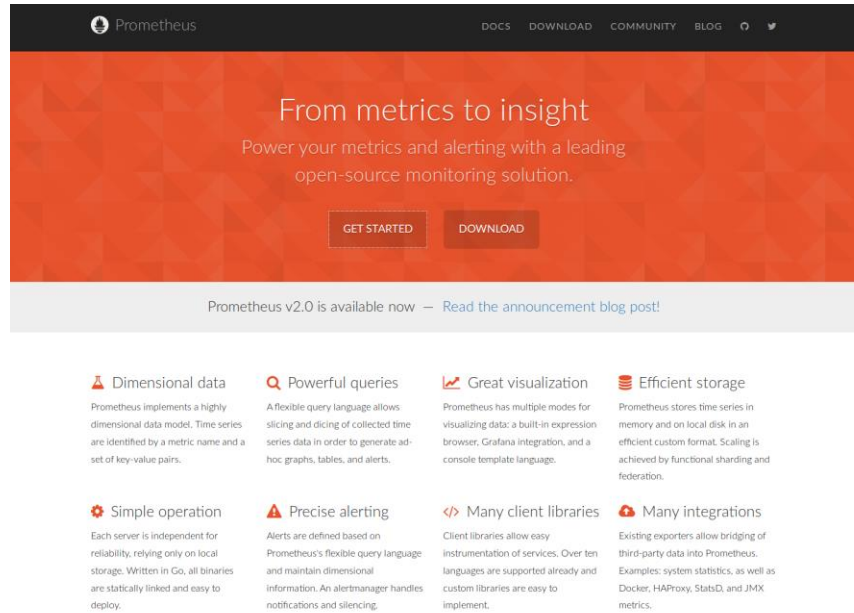
Source: https://mlcommons.org/en/training-normal-10/

Also check: https://www.benchcouncil.org/AIBench/index.html

Service/Infrastructure Monitoring Tools

There are many powerful tools!

But only low-level, well-identified monitoring information (infrastructures): pre-defined metrics exposed through interfaces with push/pull mechanism



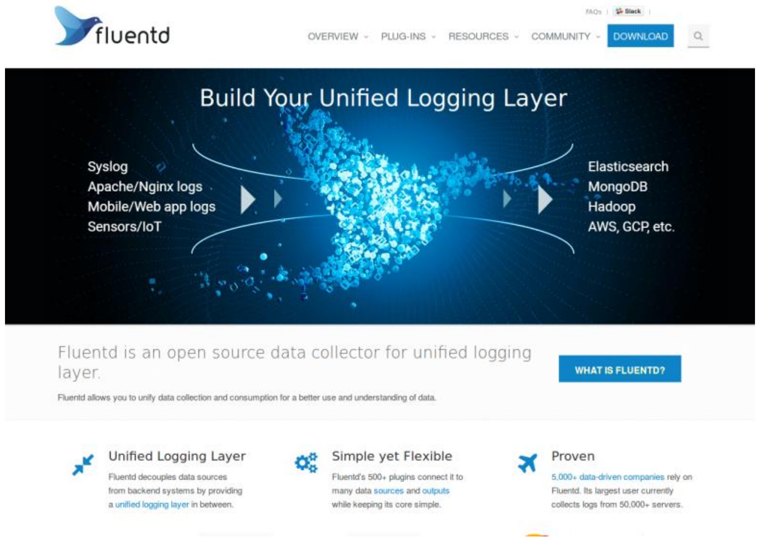
From: https://prometheus.io/

Instrumentation for Observability

Code instrumentation: for many metrics and logs that cannot be obtained from the outside of the component

→

the developer can instrument the code to capture metrics/generate logs/traces

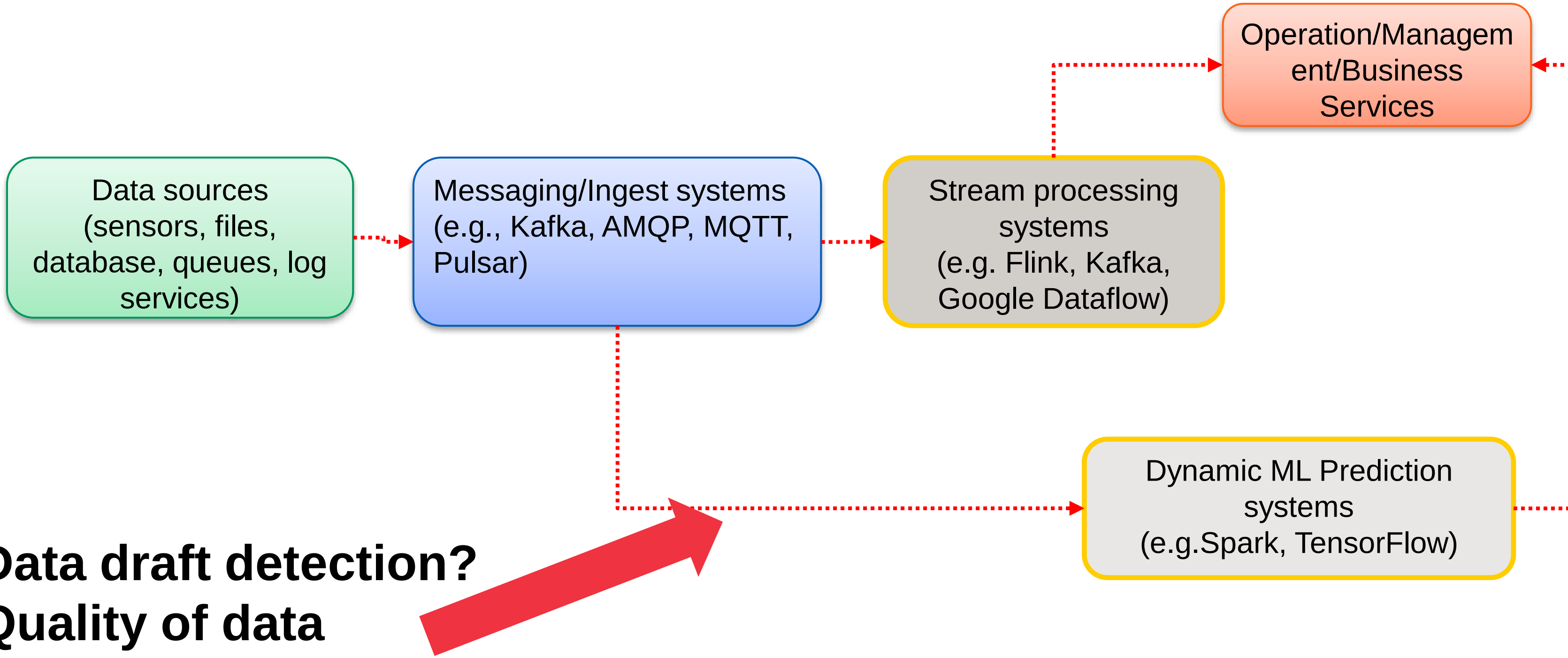


From: https://www.fluentd.org/

OpenTelemetry

https://opentelemetry.io/

Can we capture data metrics on-the-fly? For which use cases?

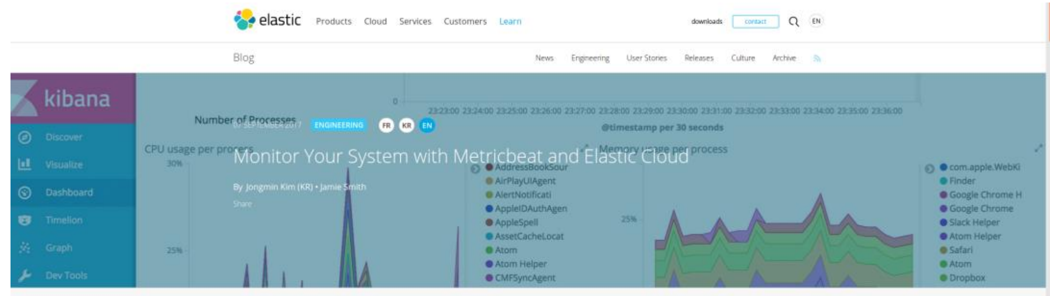


Data draft detection? Quality of data detection?

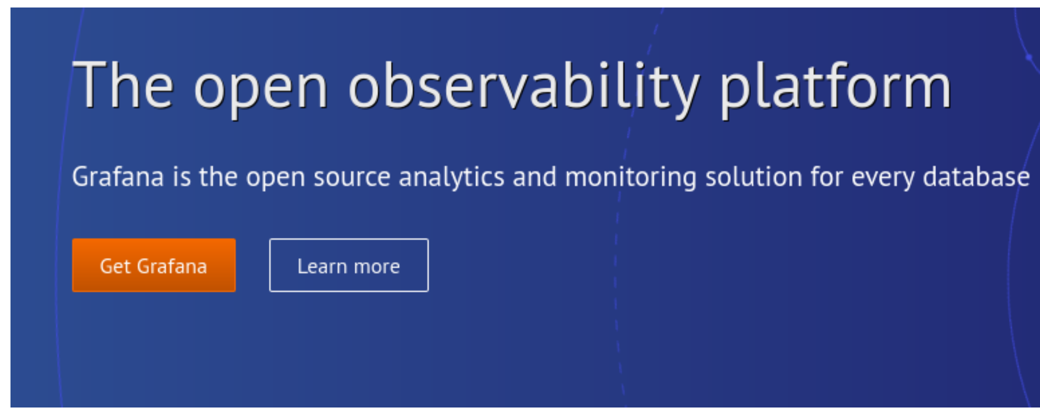
Visualization

Metrics and Visualization

- Easy to visualize many types of metrics
- But only you can specify, define and map them to your applications



https://www.elastic.co/products/kibana



https://grafana.com/

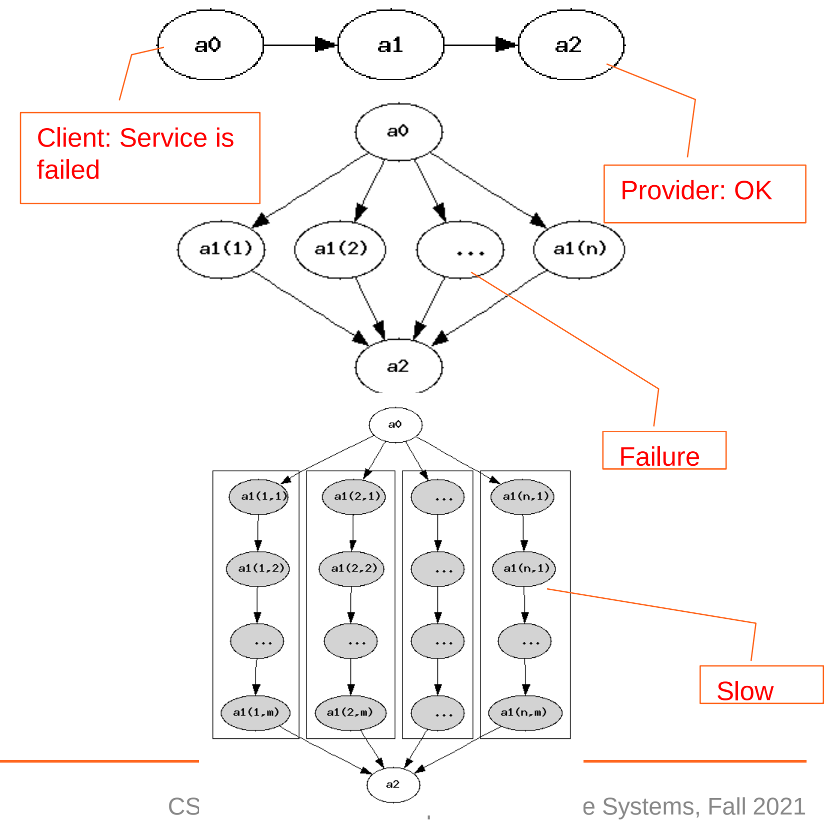
Observability

- **To monitor and understand the system as whole, end-to-end**
  - Every component must be monitored
  - Dependencies/interactions must be captured
  - Metrics, logs, tracing, etc are needed to be integrated
- **Understand the states and behaviors of the whole systems**
- **Complex problems in big data/ML systems as these systems**
  - large-scale number of microservices in large-scale virtualized infrastructures
  - multi-dimensional states (code, models and data)

Do we understand the structure of big data/ML application

- **Composable method**
  - divide a complex structure into basic common structures
  - each basic structure has different ways to analyze specific failures/metrics
- **Interpretation based on context/view**
  - client view or service provider view?
  - conformity versus specific requirement assessment

Dependency Structure



Support an end-to-end view or not

- **End-to-end reflects the entire system**
  - e.g., data reliability: from sensors to the final analytics/inference results
  - what if the developer/provider cannot support end-to-end?
- **The user expects end-to-end R3E**
  - e.g., specified in the expected accuracy
- **Providers/operators want to guarantee end-to-end quality**
  - need to monitor different parts, each has subsystems/components
  - coordination-aware assurance, e.g., using elasticity

Techniques for addressing problems in different system/software layers

- **Immutable infrastructures: containers and orchestration**
  - shared nothing for isolation, redundancy elasticity, auto-recovery
- **Services:**
  - redundancy, data/function sharding, microservices for isolation, elasticity/autoscaling-based, stateless
- **Tasks:**
  - fault-tolerance, retries, delegation
- **Interactions/Requests**
  - service-based, well-defined protocols for isolation, asynchrononous modes for isolation, elasticity, handling cascading failures

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Example:
The goal is to avoid (cascading) failures in serving requests which is a common problem

Resilience techniques have to be applied in many places (due to many types of request)

Example: resilience implementation strategies for request handling

- **Component/service replication**
  - multiple instances, both data and function sharding
- **Component/service isolation**
  - asynchronous communications among services, microservices (virtualization/containers), share nothing infrastructural design, failure isolation, well-defined protocols
- **Component/service function delegation**
  - hand over the tasks to other components through task distribution/orchestration via workflows, queues and serverless

Example: resilience implementation strategies for request handling

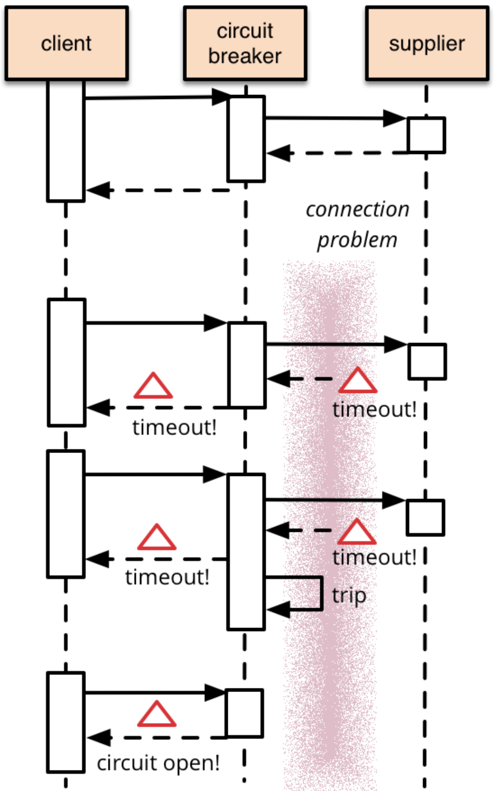
- **Throttling Pattern**
- **Circuit breaker pattern**
- **Queue-based Load Levelling Pattern**
  - https://docs.microsoft.com/en-us/azure/architecture/patterns/queue-based-load-leveling
- **Retry Pattern: exponential backoff**
  - https://cloud.google.com/iot/docs/how-tos/exponential-backoff
- **Many implementation guides and tools, e.g.**
  - https://github.com/resilience4j/resilience4j

Circuit breaker pattern

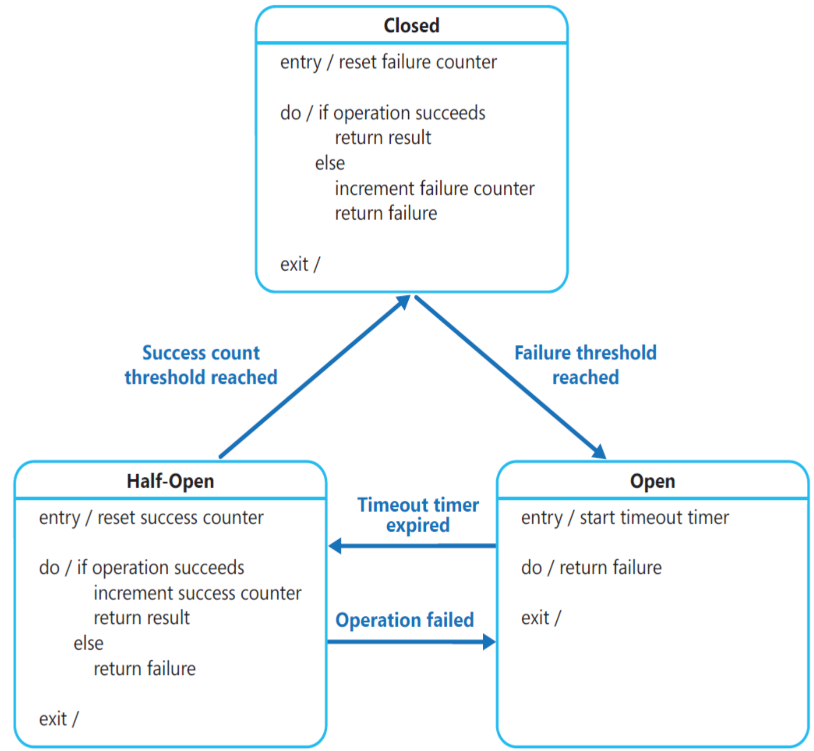
- *What if service operations fail due to unexpected problems or cascade failures (e.g. busy → timeout)*
  - Let the client retry and serve their requests may not be good

→ Circuit breaker pattern prevents clients to retry an operation that would likely fail anyway and to detect when the operation failure is resolved.

Circuit breaker patterm



Source: http://martinfowler.com/bliki/CircuitBreaker.html

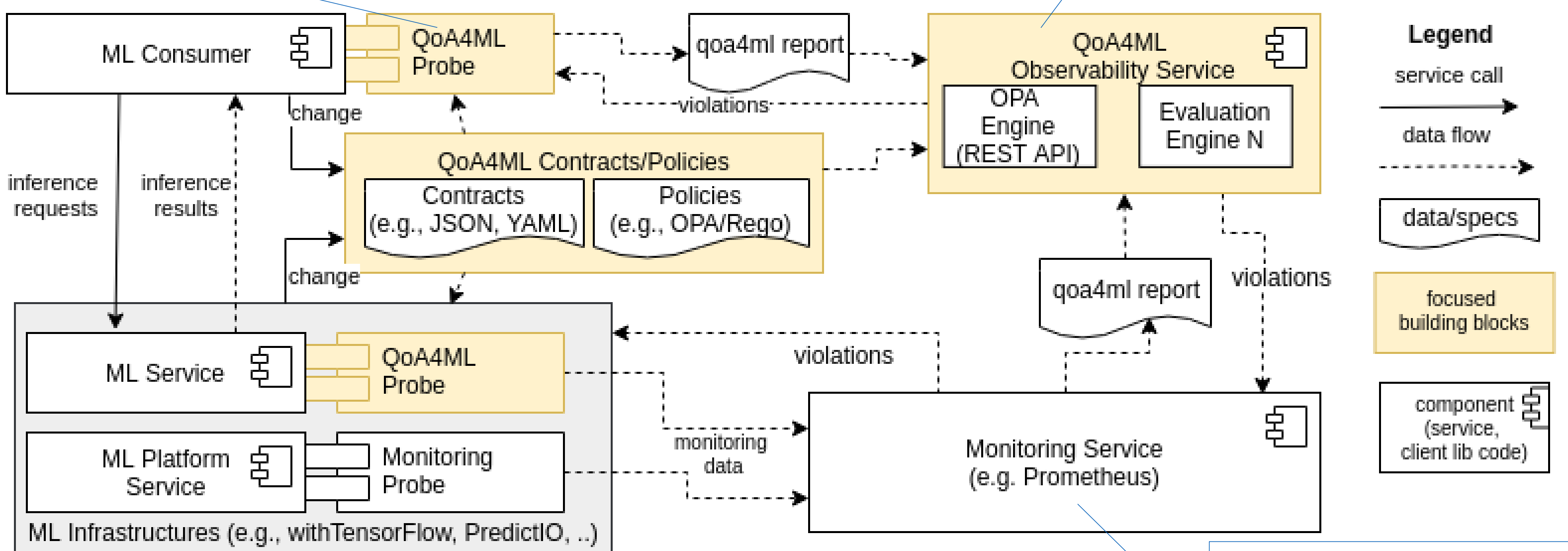


Source: https://msdn.microsoft.com/en-us/library/dn589784.aspx

ML contract observability: QoA4ML

Monitor ML-specific attributes

Design for different engines to be used



Reuse well-known monitoring systems

https://github.com/rdsea/QoA4ML

Big data/ML for Observability vs Observability for Big data/ML systems

- **Big data of metrics, logs and traces**
  - Large number of entities to be observed
  - High number of measurement dimensions
- **ML for observability**
  - Classification, prediction and detection of traffics/interactions anomaly behaviors, hidden relationships, etc.
  - Root-cause analysis
  - ML serving is   in the edge and cloud

Experiment management

how do we manage important information for ML model?

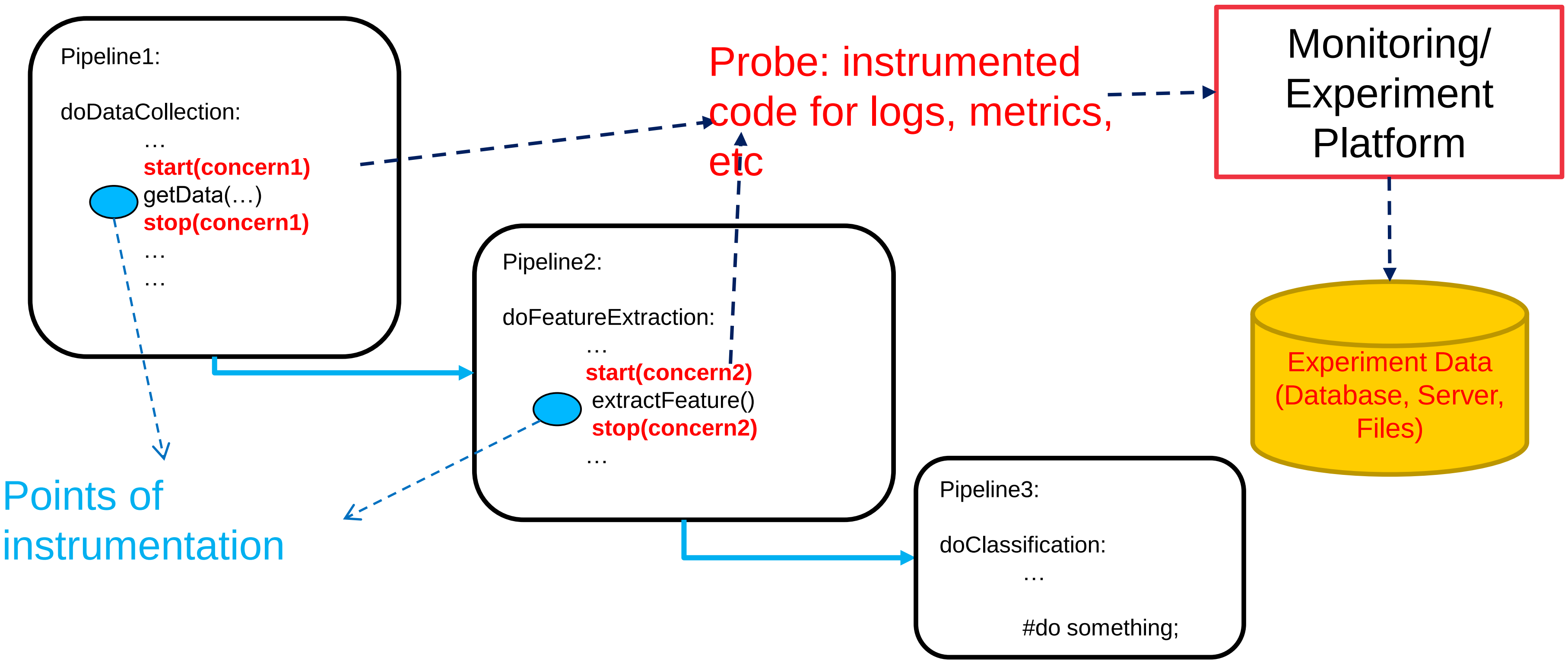
Problems

- **We need to run many experiments**
  - testability/observability purposes: figure out suitable configurations
  - how does this help to understand and support R3E?
- **Experiment management**
  - known domain and well-known books (e.g., "Design and Analysis of Experiments" by Douglas C. Montgomery)
  - principles: capturing various configurations
  - how does it work in big data and ML?
- **What do we need?**
  - tools/frameworks for tracking experiments

Notions

- **A single run/trial**
  - inputs, results, required software artefacts
  - computing resources, logs/metrics
- **Experiment**
  - a collection of runs/trials/executions gathered in a specific context
- **Steps**
  - parameterization: generate different parameters
  - deployment: prepare suitable environments
  - execution: run and collect metrics
  - analysis and sharing: analyze experiment data

Experiment tracking



But remember it is very large system! Which tools can we use?

Examples

- **Experiment in Azure ML SDK**
  - https://docs.microsoft.com/en-us/python/api/overview/azure/ml/?view=azure-ml-py#experiment
- **MLFlows https://mlflow.org/**
- **Kubeflows**
  - https://www.kubeflow.org/docs/pipelines/overview/concepts/
- **DVC: https://dvc.org/**
- **Verta: https://www.verta.ai/**

Examples: MLFlow APIs

- **Experiment**

`mflow.start_run()/end_run()`

- **Logs/metrics collection**

`mflow.set_tag()`

`mflow.log_*()`

- **Tracking data management**
  - Local files, Databases, HTTP server, Databrick logs

(follow our hands-on tutorial)

Study log 2

Describe one big data/ML pipeline that you are familiar with and explain your thoughts on how would you support the aspects of “benchmarking”, “monitoring”, “observability”, “experimenting” or “design pattern” for testing/implementing R3E aspects

- Is enough to focus on 1 pipeline and 1 aspect
- Be concrete, e.g., with metrics and possible tools
- Analyze if things can be done easily or where are the challenges that might be interesting for further investigation
- Optionally link to issues raised/addressed in a reading paper

Thanks!

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rdsea.github.io